Does Society Underestimate Women? Evidence from the Performance of Female Jockeys in Horse Racing*

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Abstract

Women are under-represented in many top jobs. We investigate whether biased beliefs about female ability - a form of 'mistake-based discrimination' - are partially responsible for this under-representation. We use more than 10 years of data on the performance of female jockeys in U.K. and Irish horse racing - a sport where, uniquely, men and women compete side-by-side - to evaluate the presence of such discrimination. The odds produced by the betting market provide a window onto society's beliefs about the abilities of women in a male-dominated occupation. We find that women are slightly underestimated, winning 0.3% more races than the market predicts. Female jockeys are underestimated to a greater extent in jump racing, where their participation is low. We discuss possible reasons for this association.

Keywords: gender, glass ceiling, discrimination, horse racing

JEL Classification: G14, J16

1 Introduction

Women are under-represented in top-ranking positions across a range of professions: within business, within politics, and within academia. This under-representation has been dubbed the 'glass ceiling', and has attracted interest from academics (e.g. Bertrand and Hallock (2001)), policymakers[1], and the popular press[2]. Furthermore, the absence of women in high-ranking positions coincides with a gender wage gap right across the wage distribution (Arulampalam *et al.* (2007)).

Explanations for unequal outcomes for men and women in the labour market are manifold. One explanation is that women are reluctant to engage in competition. Niederle and Vesterlund (2007) show that women prefer piece-rate compensation, rather than compensation determined by a competitive tournament. If the achievement of high office - whether in

[1]For example, see the British government report on increasing female representation on corporate boards (www.gov.uk/government/policies/making-companies-more-accountable-to-shareholders-and-the-public).

[2]For example, see *The Economist* on the male-dominated world of central banking (www.economist.com/news/finance-and-economics/21584386-unsteady-march-diversity).

business, politics, or elsewhere - involves performing in competitive environments, the relative absence of women at this level could be partially explained by female distaste for such competition.

Other prominent explanations can be categorised as discrimination. One example is taste-based discrimination (Becker (1957)), where discriminatory managers are willing to forgo some profitability in return for a workplace predominantly composed of men. Alternatively, such discrimination may be statistical (Phelps (1972)), in that the decision to choose a male employee over an equally qualified female employee is due to unobserved factors in individual productivity, combined with differences in the average productivity of men and women.

In this paper we investigate an alternative form of discrimination. We investigate whether society - for want of a better word, and intended to include both men and women - systematically underestimates the skills and abilities of women. Perhaps many employers mistakenly believe that women are not capable of carrying out high-powered jobs? Furthermore, perhaps the absence of women in these roles accentuates this perception, as employers do not get the opportunity to learn about the abilities of women? Wolfers (2006) labelled this type of discrimination 'mistake-based'.

To examine mistake-based discrimination, we investigate the performance of female jockeys within U.K. and Irish horse racing. This is the only major sport where men and women compete side-by-side in competition. Moreover, a betting market trades bets on the winner of each race. The betting market - and the odds it produces - therefore provides a unique window onto society's beliefs about the skills and abilities of women in a male-dominated occupation. If female jockeys are systematically underestimated, we can expect them to win more often than their odds imply, and finish races before their more heavily-favoured male competitors.

Importantly, our empirical strategy does not rely on the assumption that male and female jockeys are of equal ability, or indeed that they receive equal opportunities to ride the best horses. The analysis we present answers the simple question: given the hand that male and female jockeys have been dealt - both in terms of their individual ability, and that of their horse - does the market systematically underestimate the skills and abilities of women?

Across more than 10 years of racing in the U.K. and Ireland, involving 123,704 races and more than 1.32m competitors, we find that female jockeys are slightly underestimated; female jockeys are 0.3% more likely to win races than betting market prices predict.

This small effect, however, masks subtle differences across the sample. We find that female jockeys particularly outperform expectations in the two forms of jump racing: over hurdles, and over the more arduous obstacles in steeplechases. To be specific, female jockeys win 0.7% more hurdle races and 0.9% more steeplechases than the market predicts. Captured another way, female jockeys finish, on average, 0.3 places better than the market predicts in steeplechases and 0.54 places better in hurdles. Interestingly, female jockeys secure only 2.89% of the rides in steeplechases and 2.18% of rides in hurdle races, compared to 8.19% in all-weather flat races, for example. In Section 5 we will discuss possible reasons why female jockeys are underestimated in precisely the types of races where their participation is lowest.

Our paper is closest in spirit to those of Wolfers (2006) and Kolev (2012). Wolfers compared the stock returns of firms with a female CEO to those with a male CEO. If female CEOs are underestimated by financial markets, we would expect to accrue abnormal returns by holding the stock of firms with a female head. Wolfers actually found negative abnormal returns of firms headed by a woman when compared to the returns of firms headed by a man, but the difference was not statistically significant. This insignificance was predominantly ascribed to a lack of statistical power. In his sample there were only 64 female CEOs, compared to 4175 male CEOs, and females only worked 1.3% of the CEO-years. Kolev (2012), however, showed that an alternative construction of the data, and alternative econometric techniques, yielded statistically significant negative abnormal returns for female-led firms. In the absence of an omitted risk-factor, or mispricing lasting beyond the length of Kolev's study, there is therefore evidence to suggest that females are, in fact, overestimated by stock market participants. If that is the case, erroneous beliefs regarding female ability are unlikely to be a driver behind the large discrepancy between male and female labour market outcomes.[3]

[3] There is a parallel literature that examines stock market reactions to the appointment of a female CEO. Lee and James (2007) find a negative market response, on average, to female appointments compared to male appointments. However, others have not found such a response when randomly selecting comparator male CEOs appointment from the same industry (Gondhalekar and Dalmia (2007)), or when using matching on observables techniques (Martin *et al.* (2009)). A review of this literature can be found in Mohan (2014). Our interest is in whether market beliefs are unbiased, rather than establishing the nature of these beliefs (i.e.

Our setting, however, offers advantages over the aforementioned stock market studies. Firstly, there is greater statistical power. We have 1385 female jockeys in our sample out of a population of 6134. Although female jockeys secure fewer rides than their male counterparts, they still obtain 4.75% of the approximately 1.32m rides in our sample. A second advantage is that each jockey is not tied to any one horse in the way that a CEO is, at least temporarily, tied to one firm. Jockeys will ride different horses in the same day, and horses will also be ridden by different jockeys. We can therefore more cleanly isolate the 'value-added' by each jockey. Thirdly, while caution must be exerted in extrapolating observations from betting - an activity with negative expected returns - betting market prices may reflect the beliefs of a wider section of society. Stock returns are largely in the hands of institutional investors and money managers, while individuals 'manage their own money' in betting markets. In 2011, the British Horse Racing Authority estimated that 6.1m people attended a U.K. horse race, with a substantial proportion placing bets.[4] We hope to garner a reflection of their beliefs about female ability by examining the prices that result from these bets.

Fourth, we can measure beliefs about male and female ability at different levels of an industry. While stock market prices may reflect beliefs about the abilities of the heads of large publicly-listed firms, betting markets can tell us about the public's perceptions of a wide range of competitors, from the elite practitioners in class 1 races, all the way down to the part-timers who compete in class 7, or undesignated, races. We can use this variation to see if discrimination exists to a lesser or greater extent at the upper or lower echelons of the sport. Finally, and perhaps most importantly, betting market assets are finitely-lived. Bets are traded, the race is run, and the fundamental value of each bet is revealed. If markets underestimate women, therefore, female jockeys will simply win more races than their betting odds imply. This contrasts with stocks, which, in principle, have an infinite lifespan. If the stock market is wrong to believe that the appointment of a female CEO is bad news, there is no specific time-frame in which the market's error will be definitively revealed.

The rest of the paper is structured as follows: In Section 2 we provide some background

whether the market believes the appointment of a female is bad news or not). For this reason, our paper is more closely related to the work of Wolfers (2006) and Kolev (2012).

[4]British Horse Racing Authority FactBook 2011/12.

on the standard career progression of a jockey, and look in particular at anthropological studies of women in this role. In Section 3 we describe the institutional features of betting in the U.K. and Ireland, and review the literature on betting market efficiency. In Section 4 we present the data, with the full analysis in Section 5. Section 6 concludes.

2 The Jockey

It is common for jockeys to begin their career in horse racing in the more mundane occupation of stable hand, or 'lad' as he or she is sometimes called. The stable hand will keep the trainer's yard clean, exercise the horses, and help in the preparation for races. From here, a promising jockey can hope to ride as an amateur, which requires a license, or ideally ride as a trainer's apprentice. When riding as an apprentice - or a 'conditional', as they are called in jump racing - the jockey benefits from a reduction in the weight they must carry in races. However, once the apprentice has won a certain number of races, the allowance is dropped, and the jockey must compete with his or her professional peers on an equal footing. Once professional, a jockey can ride exclusively for a large stable, as many of the elite jockeys do, or ride freelance for a number of stables.

Even though women have held licences to ride since 1972 (Hargreaves (1994)), women can be disproportionately found as stable hands. Statistics from the British Horse Racing Authority indicate that women held 41.6% of jobs within trainers' yards in 2011. However, only 17.11% of apprentice jockeys at the time were female, and even fewer females found themselves within the professional jockey ranks.

Cassidy (2002) - in her anthropological study of life in Newmarket, the 'HQ' of horse racing - provides some insight into reasons given (by males) for the lack of progression of females. Trainers assert that male stable hands are more ambitious, and females more nurturing and conscientious in their work in the stable. Consider the following quote:

'You know what lads are like, they want to be jockeys day and night, so we stick to girls, they really care about the horses and do a good job'

Roberts and MacLean (2012), in a discourse analysis, state that the limited opportunities for female jockeys are justified, within the industry, on three grounds: physical strength, body shape, and tradition. One trainer in this study suggests that they would always prefer a male jockey over jumps, primarily due to the physical strain, but that the choice was less clear on the flat:

'I think Hayley Turner is as good as any guy riding; she rides a bit for me. There are a lot of good girls riding.'

Roberts and MacLean go on to suggest that while the prospects for women in flat racing may improve (due to the importance of being light), there is little chance of equal opportunities for women in jump racing.

As mentioned earlier, the key feature of our empirical design is that we do not have to evaluate the relative merits of male and female jockeys, either in flat racing or over jumps. Neither do we need to assume that males and females receive equal opportunities to ride the strongest horses. (The discussion above suggests that they do not). We can control for both jockey and horse ability, via the betting market odds, and ascertain whether female jockeys outperform these expectations. As a result, we can establish whether betting markets - which are populated by bookmakers, owners, trainers, jockeys, stable hands, and the betting public - hold skewed beliefs about female ability in a male-dominated environment.

3 Horse Race Betting

Punters in the U.K. and Ireland can bet on horse races in three main market structures. The first of these is the Tote, a pari-mutuel pool run until recently in the U.K. by the government, but now in the hands of a private operator. Tote Ireland is owned by the country's horse racing governing body. Pari-mutuel pools dominate wagering in the U.S. and Hong Kong, but are slightly less popular in the U.K. and Ireland (in part due to the available alternatives that we will discuss). When placing a bet in a pari-mutuel pool, the punter does not specify the price (or odds) at which they would like to trade. Instead the bettor only specifies the volume of their bet. Winnings bets are then funded from the money taken from all of the losing bets, after the operator has removed the track-take. The track-take in the U.K. was as low as 13.5% in 2003, but is now quoted at 22%. The money paid to a punter holding a winning ticket is determined by the proportion of volume on that horse for which he or she was responsible. The odds on each horse are declared when the market closes at the start of each race. The more money that is placed on a horse, relative to the competition, the lower the final odds and the lower the payout in the case of a win.

The second type of betting is facilitated by bookmakers. In contrast to pari-mutuel betting, bookmakers specify a price, or odds, that they are willing to offer. These odds can be posted in bookmaker shops on high-streets throughout the country, online, or on electronic boards with the on-course bookmakers. The volumes that can be traded at these odds are not specified, and bookmakers may refuse to take large bets for certain horses. Rather than profiting from the track-take, bookmakers' profit margins stem from the 'over-round'; i.e. if you summed up the win probabilities of all the horses in a race - implied by the bookmaker's odds - they would exceed 1. This allows bookmakers to, in expectation, make a small profit on each race. For our study, we use the Starting Price (*SP*), an average of on-course bookmaker prices at the time the race starts. These odds should be the most informative bookmaker odds, as these bookies can observe the horses and conditions at closer proximity than bookmakers located away from the racecourses. Indeed, many off-course bookmakers agree to settle bets at the *SP*.

A third form of betting markets are the betting exchanges, the largest of which is Betfair in the U.K.. Developed only in the last decade and a half, the exchanges allow for individual punters to replicate the role of bookmakers. Modelled on the structure of financial limit order books, bettors can back or lay horses. Laying a horse means betting that she or he will lose. Furthermore, these back and lay bets can be placed in the form of limit orders (or quotes for others to take the other side of the bet), or market orders (executed at quotes already provided by others on the exchange).

There are two main differences between the Tote, on the one hand, and the bookmakers and betting exchanges on the other. The first difference is that prices are not fixed at the time a bet is placed with the Tote. Projected prices, based on volume so far, are displayed on the screens prior to a race, but a large amount of money is typically wagered in the last few minutes, leading to large, and late, price swings. Secondly, there is no intermediary in pari-mutuel betting. While bookmakers and betting exchange participants set prices - which can account for volume if they think the volume is informative, or discount trading volume if they think it is not - prices in the pari-mutuel pool are solely determined by volume. These differences have two potential implications. Firstly, pari-mutuel prices may reflect the beliefs of bettors without the interjection of the views of a few bookmakers or liquidity providers on the exchanges. Secondly, if beliefs are biased against female jockeys, for example, the absence of accurate real-time price information means that it is problematic to arbitrage any discrimination against female jockeys in pari-mutuel pools. In these two senses, it would be interesting to use pari-mutuel prices to evaluate gender discrimination in horse race betting. However, records of Tote prices are often patchy (particularly for those horses that did not win races), and are not available for such a long time-frame as the bookmaker *SP* we use in this study.

For many decades researchers have used betting market data to evaluate beliefs, risk-preferences, and market efficiency. From the early work of Griffith (1949), researchers have typically noted a favourite-longshot bias, where the returns to betting on favourites exceed those of betting on longshots. This bias has been found in pari-mutuel pools (e.g. Snyder (1978), among many others), bookmaker markets (Vaughan Williams and Paton (1997)), and the betting exchanges (Smith *et al.* (2006)). Explanations range from the misestimation of win probabilities (Griffith (1949)), risk-loving behaviour (Weitzman (1965)), heterogeneous beliefs (Ali (1977)) and adverse selection (Shin (1993)). For a survey of these explanations, see Ottaviani and Sørensen (2008)). Ours is the first study, to our knowledge, to evaluate mispricing of bets due to participant gender. At the same time, we find a slight negative favourite-longshot bias which, while rare, has been found in other well-developed betting markets (e.g. Busche and Hall (1988)). In evaluating the presence of discrimination against female jockeys, we will attempt to rule out any confounding effect related to the favourite-longshot bias.

4 Data

We collected data on U.K. and Irish horse races from 1st January 2003 to the 7th September 2013 from Betwise, a betting information company. This sample includes 123,704 races with just over 1.32 million runners. The database includes a series of race variables, such as the date, time, location, class, type of race, and distance. Class is only applicable for U.K. races, and runs from 1, the elite class, to 7. The majority of races are one of 5 types. The first three of these are run on the flat. These are 1) all-weather flat races, which are run on synthetic ground, 2) (standard) flat races, which are perhaps the most prestigious, and 3) national hunt flat races, which are used to ease future jump horses into the practice of racing. The other two major types of races involve obstacles. These are 1) hurdle races, where the obstacles are relatively low, and 2) steeplechases, which involve more arduous obstacles. The Grand National, the most famous of the jump races, is a steeplechase.

Also included in our data are a number of horse-specific variables. These include the name of the horse, the name of the jockey, and the starting price (SP) for each horse in each race. As discussed in Section 3, the starting price is an average of on-course bookmaker odds at the time the race begins. The odds, which include the stake, range from 1.01 to 501. For example, a 1 GBP winning bet on a horse with an SP of 3 would lead to a payout of 3 GBP (including the return of the 1 GBP stake). The bettor would therefore have made a profit of 2 GBP. If the horse loses, the 1 GBP stake is kept by the bookmaker.

Our next procedure is to identify the female jockeys within the sample. Most of the time, this is a simple task. Most female jockeys are listed as a Miss, Mrs, or Ms in the data. However, there are certain jockeys without a title. For these we checked first names and designated the jockey as a female only after an internet search (involving the British Horse Racing Authority site, the Horse Racing Ireland site, the *Racing Post* site and other Google searches) revealed his or her gender. There were some jockeys whose identity was not clear (i.e. listed as 'Reserve', for example), and these were left out of the analysis.[5]

Our designation of jockey gender turned up 1385 females, and 4749 males. This includes amateur jockeys, apprentices (or conditionals, in jump racing), and professionals. In Table 1 we summarise the participation of women across the full sample, across years, across classes

[5] We were unable to classify the identity or gender of 1.2% of the participants in our sample. We do not find that these unidentified competitors outperform or underperform betting market expectations (with respect to male and female jockeys with similar implied win probabilities), and, further, there is little in the literature we reviewed in Section 2 to suggest that males or females disproportionately play the back-up role of Reserves (who themselves are more likely to be unidentified in our data-set). We therefore do not have reason to believe that leaving these competitors out of our analysis affects any inferences we draw.

of race, and across race types. Overall, female participation stands at 4.75% of rides. There is some evidence that this has increased over the years, going from 4.2% in 2003 to 6.2% in 2012 (the last full year in our sample). However, female participation does appear to be concentrated in lower-grade races. Females secure 7.48% of rides in class 7, but only 1.16% in the top class races. Finally, females secure a greater number of rides on the flat, particularly in the less prestigious races on synthetic surfaces (the all-weather flat races), and in national hunt flat races, which are staging posts for future jump horses. Female participation in jump races is low, with women securing 2.18% of rides in hurdle races, and 2.89% of rides in steeplechases.

We also calculated the predicted percentile of each jockey in each race, and display the average of this statistic for females in Table 1. The percentile is calculated by ordering the horses in each race from the favourite to the longest of longshots. For example, a horse with an SP of 2 is predicted to finish before a horse with an SP of 4, who is predicted to finish before a horse with an SP of 7, and so on. This predicted percentile measure indicates that female jockeys are typically longshots in races. Female jockeys are, on average, the 59.53rd percentile in races. There is not much evidence that this has changed over the years, though there is some evidence that women are more likely to ride favourites in lower class races. The average female percentile in class 7 races is 58.05, compared to 63.37 in class 1 races. Females are also more likely to ride favourites in national hunt events (including flat races) compared to all-weather and standard flat races. For example, female jockeys ride, on average, as the 49.43rd percentile in national hunt flat races.

Our first measure of race success is an indicator variable equalling 1 if the horse won the race. We want to compare this for each implied win probability, which is calculated as $1/SP$, where SP is the starting price. The idea behind this measure is that, in the absence of a bookmaker profit margin and in the case of a risk-neutral representative bettor (more on this in a moment), all bets would yield an expected return of 0. In other words, the implied win probability would approximate the empirical win probability. For example, take a series of horses with SPs of 4. The implied win probability of these horses would be $1/4 = 0.25$. Therefore, such horses should win approximately 1 out of 4 times they run. If the bettor picks up a profit of 3 GBP for each win, he or she will, in expectation, break even, by losing 1

GBP in each of the other 3 runs. Now, if there is a positive bookmaker margin, implied win probabilities will actually slightly overestimate empirical win probabilities. Furthermore, if the representative bettor is risk-loving (or alternatively, risk-averse), we will observe a positive (negative) favourite-longshot bias. This is because a risk-loving (risk-averse) bettor is willing to pay a premium, in terms of lower expected returns, in return for betting on a low (high) win probability horse. We will keep an eye on both of these potential frictions - the bookmaker margin, and the risk preferences of the representative bettor - in our upcoming empirical analysis.

In Figure 1 we plot the average race win indicator for each implied win probability (rounded to 2 decimal places). We compare this plot for male jockeys (dots) and female jockeys (diamonds). If women are systematically underestimated, we should observe more female dots above the male dots (for any implied win probability). To put this another way, if the betting market underestimates female jockeys, a section of female jockeys predicted to win 25% of the time (i.e. with odds of 4), for example, would actually win 24% of the time, compared to male jockeys with the same odds who only win 23% of the time. Such an example allows for a bookmaker profit margin, but implies that the margin would be smaller for female jockeys if they are underestimated relative to men. Where the data are plentiful (at the lower implied win probabilities), however, it would appear that male and female jockeys, with the same odds, win approximately as often as each other. As we move towards higher implied win probabilities, it is clear that the data for women becomes more noisy. This is due to the absence of sufficient female favourites. Nevertheless, there is no clear graphical evidence from the full sample that women are systematically underestimated relative to men.

The problem with our first measure of race success is that it is relatively coarse. All of those that fail to win the race receive the same measure of success: a 0 in the win indicator column. This ignores potential differences in how each horse and jockey performed relative to market expectations. With this in mind, we also consider the predicted and actual finishing positions of male and female jockeys.

The predicted position is calculated by ordering the horses by their win odds, as with the predicted percentile measure. In Figure 2 we plot the average actual finishing position for each predicted finishing position. Male (Female) jockeys are displayed with dots (diamonds). We truncate the analysis at the top 20 predicted positions as few races have more than 20 competitors. An important thing to note is that, aside from the favourites (who can only underperform), horses that finish tend to outperform expectations, simply by finishing. There are a substantial number of horses that are pulled-up during races (and therefore do not have a finishing position). Those that do complete the race, therefore, tend to jump a few places. More importantly, we find little graphical evidence from the full sample that female jockeys outperform expectations in terms of finishing position. If female jockeys are systematically underestimated we would expect to find female dots below their male equivalents (i.e. for each predicted position female jockeys would finish a rank or two higher). However, there is little from the plots of the full sample to suggest that there is a such a general underestimation of women.

We intend that our two measures of race success capture female jockey performance relative to expectations in a way that is intuitive for the industry. With this in mind, consider the following quote regarding a win for Hayley Turner (perhaps the most famous current female jockey) from the *Guardian* on 30th April 2008:

'The few racegoers not swept from the grandstand steps by driving rain at Bath could have found little fault with Turner's winning effort on Rose Row in the staying handicap.....That victory, on the fifth-favourite in a field of seven, showed Turner can make the most of her opportunities.'

Such a performance would show up as 1 in the win indicator column, on a horse incidentally with a win probability of only 0.117 (SP of 8.5), and also a finishing position of 1st despite being ranked 5th prior to the race. This is precisely the type of outperformance - if replicated for women across the sample - which would indicate a systematic underestimation of their abilities.

In the same vein is this quote regarding Lucy Alexander, a jump jockey, in the *Telegraph* on 7th December 2011:

'Last month she rode three winners in four days and at Musselburgh on Monday she landed her first double. Punters will be keen on her because, to a 1 pound stake, her rides have produced a return of plus 41 pounds this season. Without getting on favourites she is

getting results.'

In other words, in this very small sample, one female jockey is winning substantially more often than her odds would suggest. In the next section we will formally test whether the market underestimates women across a much larger sample of women, and across the full 10 years.

5 Analysis

We begin our analysis by assessing whether female jockeys win races more often than their odds imply. If they do, this would suggest that the market underestimates their ability to get the best out of their horse. In the first column of Table 2, we regress an indicator variable equalling 1 if the horse in question won the race, on the implied win probability of the horse (calculated from the starting price), and an indicator variable equalling 1 if the jockey was female. All 1.32 million observations are included, an OLS specification is used, and heteroskedastity-consistent standard errors are clustered at both the jockey-level and the horse-level. By clustering both at the jockey and horse level - see Cameron *et al.* (2011) for the methods used - we allow for error correlations for different jockeys riding the same horse, and also error correlations for different horses ridden by the same jockey. The OLS model utilised provides easy to interpret coefficients. We would expect the intercept to be negative to allow for a bookmaker profit margin. Furthermore, in an efficient market (i.e. with no favourite-longshot bias), we would expect the coefficient associated with implied win probability to be close to 1.

Examining these results, we find that the intercept is indeed negative (-0.15), but that the implied win probability coefficient is 0.965, significantly different from 1 statistically. This indicates that there is a slight negative favourite-longshot bias. This means, once you account for the bookmaker margin, in our data longshots (favourites) win more (less) often than their odds suggest. (A coefficient above 1 would indicate a positive favourite-longshot bias, where favourites win more often than their odds suggest. We will return to this in a moment). Importantly, we find that that there is a small significant effect attached to the female jockey indicator. Female jockeys win 0.3% more races than their odds imply. While this effect was too small to decipher graphically, our regression suggests that female jockeys are slightly underestimated by the betting market when we consider the full sample.

Returning to the negative favourite-longshot bias, it is possible that the significance of the female jockey indicator is in part due to the fact that females are disproportionately longshots in the races in which they compete (see the percentile evidence in Table 1). If this is the case, we would be confounding an underestimation of female ability with a general, gender unrelated, bias in betting prices. One way to examine this possibility is to interact the female jockey dummy with implied win probability. If female jockeys appear to be underestimated simply because they are often longshots, then we should observe that the effect is greatest for female jockeys who have low implied win probabilities. In the second column of the top panel of Table 2 we present the results of this regression. We actually find that there is greater underestimation of female ability for favourites (those with high implied win probabilities), if anything, as shown by the positive coefficient associated with the interaction term. While the interaction is statistically insignificant, the female jockey indicator retains its significance at the 10% level. In short, there is slight evidence of female underestimation, in terms of wins, and little of this appears to be related to any general favourite-longshot bias in betting prices.

In the previous section we discussed how measuring a horse's finishing position may be preferable to the win indicator measure as it captures finer information about the performance of all horses relative to expectations. In the bottom panel of Table 2, therefore, we examine how finishing position varies across jockey gender. We regress finishing position on the predicted position of the horse (inferred from an ordering of betting odds), and an indicator variable equalling 1 if the jockey riding the horse was female. All observations are included in the regression, though there are only 1.22 million observations in this regression as certain horses failed to finish their race. An OLS specification is again used, and heteroskedasticity-consistent standard errors are clustered at both the jockey and horse level. We find that female jockeys finish only 0.04 places higher than the market predicts, a mispricing which is statistically insignificant. In the second column of the bottom panel of Table 2, we also interact predicted finishing position with the female jockey dummy, to ascertain whether there is a significant difference in the mispricing for those predicted to finish well and those with lesser prospects in the same race. We find no significant difference. To sum up at this stage, while there is a slight underestimation of women in the full sample in terms of wins (0.3%), there is little or no effect to be found in terms of placings.

For the remainder of the analysis we will consider a number of sub-samples. Our first hypothesis is that discrimination occurred in earlier years. The 2000s was an important decade for female participation in horse racing. In 2008, Hayley Turner became the first woman to win 100 flat races in a season. This followed her success in 2005, when she was joint Champion Apprentice. It is possible that female ability was underestimated earlier in our sample, before the achievements of this era's most successful female jockey conveyed information to the betting market about the general merits of female jockeys.

With this in mind, in Table 3a we repeat the first win indicator regression, but this time break the sample down year by year. In Table 3b, we conduct a similar exercise by repeating the finishing position regression for each year. From these results, there is little evidence that any bias in beliefs has shifted over the period of our sample. Female jockeys won 0.4% more often that their odds suggested in 2012, and gained 0.11 places, on average, relative to expectations in 2011. However, there is no evidence to suggest that female jockeys were underestimated - either in terms of wins or placings relative to expectations - in the early years.

Another hypothesis is that biased beliefs may be more prevalent (or at least easier to observe) in lower class races. This may be due to one of two factors. Firstly, with less money at stake in lower class races, there is arguably less incentive for bettors (and bookmakers) to acquire detailed information on jockey (and horse) ability. (Information may also be harder to obtain at the lower end of the sport, as the races and participants have a lower profile). Secondly, if there is a mispricing (of which an underestimation of women is just one example), smaller betting markets are less attractive to arbitrageurs looking to correct inefficiencies. Chordia *et al.* (2008) present evidence from financial markets to suggest that liquidity encourages arbitrage and market efficiency. Without such liquidity in the betting markets on lower class races, we may be more likely to observe biased beliefs about female ability.

To this end, in Tables 4a and 4b we repeat the analysis of Table 2, but this time break the sample down by class. (We lose some data as all Irish races, and some U.K. races, do not have a designated class). The results for the full sample are retained in these tables for comparison purposes. There is little evidence that females jockeys are underestimated in low class races. There is some overestimation of female jockeys in terms of wins (2%) and places (0.32 positions) in class 1 races, but the effect quickly reverses as female jockeys are underestimated by a larger 0.55 places in class 2 races, which are also elite events. It is difficult, therefore, to discern any clear pattern between class and female over/under estimation.

Our final hypothesis relates to race type. As discussed in Section 2, races can be run on the flat and over jumps. Female participation is much lower in jump racing (hurdles and steeplechases), than it is on the flat (see Table 1). Even within flat races, there are marked differences in female participation rates. Women get more rides on all-weather tracks and in national hunt flat races than they do in the classical flat races. It is possible that an underestimation of female ability is in some way connected with rates of participation.

With this in mind, in Tables 5a and 5b we repeat the regressions of Table 2, but this time with the sample broken down by race type. As before, wins are considered in Table 5a, with finishing position relative to predicted position in Table 5b. For wins, we find above average underestimation for two of the race types. Female jockeys win 0.7% more hurdle races than the market predicts, and 0.9% more steeplechases. Female participation in these two forms of jump racing is low, standing at 2.18% and 2.89% for hurdles and steeplechases respectively. A similar, and perhaps more dramatic, picture emerges in terms of finishing positions. Female jockeys finish, on average, 0.54 places better than predicted in hurdle races, and 0.3 places better in steeplechases. To put the size of this effect in context, we recreated Figure 2 in Figure 3, but this time only included jump racing. For almost all predicted finishing positions displayed, except the favourite, female jockeys outperform their male equivalents on average. In other words, the predicted placings implied by an ordering of betting market prices underestimate the abilities of female jockeys in jump racing.

Why might the underestimation of female jockeys occur in races where female participation is low? To our mind, there are at least three possible explanations. One possibility is that there is a confounding factor which drives both low rates of female participation, and a small underestimation of female ability. For example, the physicality of jump racing may create the impression that females are unsuitable as jump jockeys (see the discussion in Section 2), and also cause bettors to underestimate female ability. In other words, the two outcomes go hand-in-hand, but are actually caused by a third factor. Another possibility - and in fact the initial hypothesis in our study - is that low rates of female participation (in the job market more generally) are caused by systematic underestimation of female ability. In the case of horse racing, this would suggest that the betting market reveals a bias in the industry's beliefs, and it is this bias that leads to low levels of female employment in this particular part of the industry. A final possibility is that low levels of female participation actually lead to underestimation. It is possible that bettors are only able to accurately assess female ability if they receive sufficient signals regarding the quality of female jockeys. In the absence of enough signals (i.e. enough female jockeys), the betting market (and the industry) continue to hold mistaken beliefs, and, in turn, female participation continues to be low. Without a clean instrument - such as the exogeneous imposition of a female quota, for example - we are unable to distinguish between these explanations.

6 Conclusion

We use data from 123,704 horse races spread over more than 10 years to investigate whether society holds biased beliefs about the abilities of women. Just as in business, politics and academia, men and women compete side-by-side. The difference in horse racing is that members of the public periodically enter the workplace, and trade bets on the winners and losers. The prices that result from these bets provide a unique window onto society's beliefs about female ability in a male-dominated occupation. If women are underestimated, we should observe female jockeys winning more often than their odds imply, and finishing races before their more heavily-favoured male peers.

We compare the performance of men and women - relative to betting market expectations - both in terms of wins and final placings. For the full sample, we find that the market slightly underestimates women, who win 0.3% more races than predicted. However, this small effect masks differences across race types. Women are underestimated to a greater extent in steeplechases - winning 0.9% more races than predicted, and in hurdles - finishing, on average, 0.54 places higher than predicted. Both of these are forms of jump racing, where female participation is low.

Nevertheless, we should be cautious in extrapolating these results to other occupations. Male and female jockeys compete on a largely physical basis, while most gender competition in the workplace involves only mental tasks. In other words, mistake-based discrimination may not arise in a more typical occupation, where differences between men and women are less obvious. On the other hand, it should be noted that the betting market is an arena where discrimination is uniquely costly. If certain bettors discriminate against women, and therefore overbet on male jockeys, their money will be quickly lost. What's more, informed arbitrageurs can step in, bet on female jockeys, and destroy any remnant of the initial discrimination. It is debatable whether firms can so easily arbitrage discrimination against women in other workplaces. In other words, if mistake-based discrimination were to arise in other occupations, it may be more persistent.

References

- Ali, M., M., (1977). Probability and Utility Estimates for Racetrack Bettors. *Journal of Political Economy*, 85, 803-815.

- Arulampalam, W., Booth, A., L., Bryan, M., L., (2007). Is There a Glass Ceiling Across Europe? Exploring the Gender Pay Gap Across the Wage Distribution. *Industrial and Labor Relations Review*, 60, 163-186.

- Becker, G., S., (1957). *The Economics of Discrimination.* University of Chicago Press.

- Bertrand, M., Hallock, K., F., (2001). The Gender Gap in Top Corporate Jobs. *Industrial and Labor Relations Review*, 55, 3-21.

- Busche, K., Hall, C., D., (1988). An Exception to the Risk Preference Anomaly. *Journal of Business*, 61, 337-346.

- Cameron, A., C., Gelbach, J., B., Miller, D., L., (2011). Robust Inference With Multiway Clustering. *Journal of Business and Economic Statistics*, 29, 238-249.

- Cassidy, R., (2002). *The Sport of Kings: Kinship, Class and Thoroughbred Breeding in Newmarket*, Cambridge University Press.

- Chordia, T., Roll, R., Subrahmanyam, A., (2008). Liquidity and Market Efficiency. *Journal of Financial Economics*, 87, 249-268.

- Gondhalekar, V., Dalmia, S., (2007). Examining the Stock Market Response: A Comparison of Male and Female CEOs. *International Advances in Economic Research*, 13, 395-396.

- Griffith, R., M., (1949). Odds Adjustments by American Horse-Race Bettors. *The American Journal of Psychology*, 62, 290-294.

- Hargreaves, J., (1994). *Sporting Females: Critical Issues in the History and Sociology of Women's Sport*, Routledge.

- Kolev, G., I., Underperformance by Female CEOs: A More Powerful Test. *Economics Letters*, 117, 436-440.
- Lee, P., M., James, E., H., (2007). She'-E-Os: Gender Effects and Investor Reactions to the Announcements of Top Executive Appointments. *Strategic Management Journal*, 28, 227-241.
- Martin, A., D., Nishikawa, T., Williams, M., A., (2009). CEO Gender: Effects on Valuation and Risk. *Quarterly Journal of Finance and Accounting*, 48, 23-40.
- Mohan, N., (2014). A Review of the Gender Effect on Pay, Corporate Performance and Entry into Top Management. *International Review of Economics and Finance*, 34, 41-51.
- Niederle, M., Vesterlund, L., (2007). Do Women Shy Away From Competition? Do Men Compete Too Much? *Quarterly Journal of Economics*, 122, 1067-1101.
- Ottaviani, M., Sørensen, P., N., (2008), The Favorite-Longshot Bias: An Overview of the Main Explanations. *Handbook of Sports and Lottery Markets*, North Holland, edited by Hausch, D., B., Ziemba, W., T., 83-101.
- Phelps, E., S., (1972). The Statistical Theory of Racism and Sexism. *American Economic Review*, 62, 659-661.
- Roberts, L., J., MacLean, M., (2012). Women in the Weighing Room: Gendered Discourses of Exclusion in English Flat Racing. *Sport in Society*, 15, 320-334.
- Shin, H., S., (1993). Measuring the Incidence of Insider Trading in a Market for State-Contingent Claims. *The Economic Journal*, 103, 1141-1153.
- Smith, M., A., Paton, D., Vaughan Williams, L., (2006). Market Efficiency in Person-to-Person Betting. *Economica*, 73, 673-689.
- Snyder, W., W., (1978). Horse Racing: Testing the Efficient Markets Model. *Journal of Finance*, 33, 1109-1118.

- Vaughan Williams, L., Paton, D., (1997). Why is there a Favourite-Longshot Bias in British Racetrack Betting Markets? *The Economic Journal*, 107, 150-158.

- Weitzman, M., (1965). Utility Analysis and Group Behavior: An Empirical Study. *Journal of Political Economy*, 73, 18-26.

- Wolfers, J., (2006). Diagnosing Discrimination: Stock Returns and CEO Gender. *Journal of the European Economic Association*, 4, 531-541.

Tables & Figures

Table 1: Female Participation and Percentiles

All	Participation	Average Percentile	Total N
	4.75%	59.53	1,323,135
Year	**Participation**	**Average Percentile**	**Total N**
2003	4.20%	59.89	111,686
2004	4.65%	59.84	122,260
2005	4.43%	59.40	125,768
2006	4.09%	59.45	126,125
2007	4.20%	61.02	126,882
2008	4.54%	59.02	132,618
2009	4.20%	59.82	126,665
2010	4.83%	59.96	125,077
2011	5.50%	58.69	124,025
2012	6.20%	58.71	118,821
2013	5.75%	59.63	83,208
Class	**Participation**	**Average Percentile**	**Total N**
1	1.16%	63.37	53,941
2	3.05%	62.59	55,667
3	3.21%	61.46	84,949
4	3.23%	62.69	252,420
5	5.75%	61.33	296,886
6	8.99%	59.62	192,544
7	7.48%	58.05	23,851
Race Type	**Participation**	**Average Percentile**	**Total N**
All-Weather Flat	6.75%	61.75	229,042
Flat	5.62%	61.35	533,701
National Hunt Flat	8.19%	49.43	65,122
Hurdle	2.18%	56.30	322,660
Steeplechase	2.89%	54.63	172,476

Statistics on the participation and the average predicted percentiles of female jockeys in horse races in the U.K. and Ireland from 1st January 2003 to 7th September 2013 inclusive. Participation is defined as the proportion of rides secured by a female jockey, and predicted percentile is calculated for each participant in each race. As an example, a jockey/horse predicted to finish 6th out of 10 runners (by an ordering of his/her odds) would be the classified as the 60th percentile. Total N includes all riders, whether male or female. Statistics are displayed for all female riders in the top panel, then broken down by year, class (1 top, 7 bottom), and race type in successive panels.

Table 2: Wins & Positions (All Races)

Dep. Var.: Race Win Indicator	All	All
Intercept	-0.015***	-0.015***
	(0.000)	(0.000)
Implied Win Probability	0.965***	0.965***
	(0.003)	(0.004)
Female Jockey	0.003*	0.002.
	(0.001)	(0.001)
Implied Win Probability*Female Jockey		0.006
		(0.014)
R^2	0.129	0.129
No. of Clusters (Jockeys)	6,134	6,134
No. of Clusters (Horses)	114,883	114,883
No. of Observations	1,323,135	1,323,135
Dep. Var.: Finishing Position	**All**	**All**
Intercept	2.624***	2.623***
	(0.024)	(0.025)
Predicted Position	0.561***	0.561***
	(0.002)	(0.002)
Female Jockey	-0.044	-0.020
	(0.049)	(0.078)
Predicted Position*Female Jockey		-0.003
		(0.008)
R^2	0.333	0.333
No. of Clusters (Jockeys)	5,932	5,932
No. of Clusters (Horses)	111,821	111,821
No. of Observations	1,225,878	1,225,878

Regressions to establish whether female jockeys win more often than their odds imply, and/or finish in better positions than the market predicts. In the top panel, an indicator variable equalling 1 if the horse won the race, was regressed on the implied win probability of the horse (defined as $1/SP$ where SP is the starting price), and an indicator equalling 1 if a female jockey rode the horse. In the bottom panel, the finishing position of the horse was regressed on the predicted finishing position of the horse (inferred from an ordering of the horses by betting odds), and an indicator equalling 1 if a female jockey rode the horse. Interactions were added in the second regressions. An OLS specification was used, heteroskedasticity-consistent standard errors (clustered for each jockey and each horse) are in parentheses, and *, * and . indicates significance at the 0.1%, 5%, and 10% level respectively.**

Table 3a: Wins (Year Sub-Samples)

Dep. Var.: Race Win Indicator	All	2003	2004	2005	2006	2007
Intercept	-0.015***	-0.019***	-0.016***	-0.016***	-0.016***	-0.016***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Implied Win Probability	0.965***	0.979***	0.965***	0.967***	0.976***	0.966***
	(0.003)	(0.011)	(0.012)	(0.011)	(0.010)	(0.010)
Female Jockey	0.003*	0.005	0.001	0.003	-0.001	0.005
	(0.001)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
R^2	0.129	0.144	0.124	0.112	0.128	0.128
No. of Clusters (Jockeys)	6,134	1,772	1,710	1,658	1,753	1,811
No. of Clusters (Horses)	114,883	23,066	24,537	25,438	26,265	27,036
No. of Observations	1,323,135	111,686	122,260	125,768	126,125	126,882
Dep. Var.: Race Win Indicator	2008	2009	2010	2011	2012	2013
Intercept	-0.015***	-0.015***	-0.014***	-0.013***	-0.014***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Implied Win Probability	0.956***	0.966***	0.963***	0.956***	0.961***	0.962***
	(0.010)	(0.012)	(0.012)	(0.009)	(0.010)	(0.010)
Female Jockey	0.005	0.001	0.000	0.005	0.004.	0.000
	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
R^2	0.124	0.131	0.127	0.130	0.129	0.137
No. of Clusters (Jockeys)	1,887	1,836	1,857	1,738	1,622	1,438
No. of Clusters (Horses)	28,123	27,250	26,953	25,814	24,760	21,030
No. of Observations	132,618	126,665	125,077	124,025	118,821	83,208

Regressions to establish whether female jockeys win more often than their odds imply, this time looking at racing in different years. An indicator variable equalling 1 if the horse won the race, was regressed on the implied win probability of the horse (defined as $1/SP$ where SP is the starting price), and an indicator equalling 1 if a female jockey rode the horse. An OLS specification was used, heteroskedasticity-consistent standard errors (clustered for each jockey and each horse) are in parentheses, and * and . indicates significance at the 0.1%, and 10% level respectively. The first regression uses data from all years, with subsequent regressions breaking the data down year by year.**

Table 3b: Positions (Year Sub-Samples)

Dep. Var.: Finishing Position	All	2003	2004	2005	2006	2007
Intercept	2.624***	2.648***	2.791***	2.828***	2.725***	2.746***
	(0.024)	(0.045)	(0.045)	(0.040)	(0.035)	(0.034)
Predicted Position	0.561***	0.579***	0.560***	0.556***	0.557***	0.558***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Female Jockey	-0.044	0.055	-0.009	0.083	-0.038	0.005
	(0.049)	(0.108)	(0.086)	(0.094)	(0.097)	(0.098)
R^2	0.333	0.347	0.323	0.325	0.335	0.339
No. of Clusters (Jockeys)	5,932	1,698	1,656	1,598	1,689	1,747
No. of Clusters (Horses)	111,821	21,967	23,370	24,422	25,082	25,911
No. of Observations	1,225,878	102,725	112,495	115,881	115,915	117,724
Dep. Var.: Finishing Position	2008	2009	2010	2011	2012	2013
Intercept	2.705***	2.651***	2.565***	2.474***	2.490***	2.372***
	(0.032)	(0.032)	(0.032)	(0.034)	(0.031)	(0.027)
Predicted Position	0.555***	0.552***	0.555***	0.561***	0.550***	0.554***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Female Jockey	-0.087	-0.041	-0.087	-0.110.	-0.020	0.013
	(0.085)	(0.084)	(0.078)	(0.058)	(0.083)	(0.067)
R^2	0.321	0.303	0.335	0.342	0.328	0.338
No. of Clusters (Jockeys)	1,801	1,768	1,787	1,698	1,564	1,396
No. of Clusters (Horses)	26,850	26,079	25,897	24,878	23,868	20,300
No. of Observations	122,312	117,427	116,719	115,640	111,132	77,908

Regressions to establish whether female jockeys perform better than the betting market predicts, this time looking at racing in different years. The finishing position of the horse, was regressed on the predicted finishing position of the horse (inferred from an ordering of the horses by betting odds), and an indicator equalling 1 if a female jockey rode the horse. An OLS specification was used, heteroskedasticity-consistent standard errors (clustered for each jockey and each horse) are in parentheses, and *, and . indicates significance at the 0.1%, and 10% level respectively. The first regression uses data from all years, with subsequent regressions breaking the data down year by year.**

Table 4a: Wins (Class Sub-Samples)

Dep. Var.: Race Win Indicator	All	1	2	3
Intercept	-0.015***	-0.010***	-0.010***	-0.009***
	(0.000)	(0.002)	(0.002)	(0.002)
Implied Win Probability	0.965***	0.949***	0.947***	0.934***
	(0.003)	(0.017)	(0.019)	(0.013)
Female Jockey	0.003*	-0.020**	-0.001	0.007
	(0.001)	(0.006)	(0.004)	(0.004)
R^2	0.129	0.140	0.096	0.110
No. of Clusters (Jockeys)	6,134	1,127	1,482	1,776
No. of Clusters (Horses)	114,883	15,788	16,743	25,465
No. of Observations	1,323,135	53,941	55,667	84,949
Dep. Var.: Race Win Indicator	4	5	6	7
Intercept	-0.011***	-0.012***	-0.013***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.003)
Implied Win Probability	0.958***	0.962***	0.962***	0.977***
	(0.007)	(0.007)	(0.009)	(0.031)
Female Jockey	0.002	0.003	0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.006)
R^2	0.138	0.134	0.116	0.094
No. of Clusters (Jockeys)	2,482	3,222	3,020	1,072
No. of Clusters (Horses)	56,610	64,109	45,549	8,608
No. of Observations	252,420	296,886	192,544	23,851

Regressions to establish whether female jockeys win more often than their odds imply, this time analysing different classes of race. An indicator variable equalling 1 if the horse won the race, was regressed on the implied win probability of the horse (defined as $1/SP$ where SP is the starting price), and an indicator equalling 1 if a female jockey rode the horse. An OLS specification was used, heteroskedasticity-consistent standard errors (clustered for each jockey and each horse) are in parentheses, and *, **, and * indicates significance at the 0.1%, 1%, and 5% level respectively. The first regression uses data from all classes, with subsequent regressions breaking the data down class by class. 1 is the top class, and 7 the bottom.**

Table 4b: Positions (Class Sub-Samples)

Dep. Var.: Finishing Position	All	1	2	3
Intercept	2.624***	2.627***	3.203***	2.427***
	(0.024)	(0.043)	(0.082)	(0.040)
Predicted Position	0.561***	0.521***	0.543***	0.520***
	(0.002)	(0.006)	(0.006)	(0.005)
Female Jockey	-0.044	0.318**	-0.545**	0.252.
	(0.049)	(0.107)	(0.191)	(0.129)
R^2	0.333	0.327	0.308	0.292
No. of Clusters (Jockeys)	5,932	1,092	1,373	1,684
No. of Clusters (Horses)	111,821	15,092	15,826	23,935
No. of Observations	1,225,878	49,942	52,160	76,436
Dep. Var.: Finishing Position	4	5	6	7
Intercept	2.309***	2.493***	2.819***	3.224***
	(0.033)	(0.023)	(0.024)	(0.048)
Predicted Position	0.549***	0.550***	0.535***	0.487***
	(0.004)	(0.003)	(0.003)	(0.007)
Female Jockey	-0.033	-0.026	-0.078.	0.019
	(0.099)	(0.045)	(0.047)	(0.081)
R^2	0.330	0.321	0.293	0.253
No. of Clusters (Jockeys)	2,395	3,114	2,941	1,044
No. of Clusters (Horses)	53,696	61,457	44,148	8,181
No. of Observations	226,511	276,808	187,185	22,455

Regressions to establish whether female jockeys perform better than the betting market predicts, this time analysing different classes of race. The finishing position of the horse, was regressed on the predicted finishing position of the horse (inferred from an ordering of the horses by betting odds), and an indicator equalling 1 if a female jockey rode the horse. An OLS specification was used, heteroskedasticity-consistent standard errors (clustered for each jockey and each horse) are in parentheses, and *, ** and . indicates significance at the 0.1%, 1% and 10% level respectively. The first regression uses data from all classes, with subsequent regressions breaking the data down class by class. 1 is the top class, and 7 the bottom.**

Table 5a: Wins (Race Type Sub-Samples)

Dep. Var.: Race Win Indicator	All	All-Weather Flat	Flat	NH Flat	Hurdle	Chase
Intercept	-0.015***	-0.013***	-0.014***	-0.017***	-0.017***	-0.016***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Implied Win Probability	0.965***	0.953***	0.963***	0.938***	0.972***	0.976***
	(0.003)	(0.009)	(0.005)	(0.015)	(0.006)	(0.008)
Female Jockey	0.003*	-0.001	0.003*	-0.003	0.007**	0.009*
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
R^2	0.129	0.116	0.117	0.141	0.153	0.130
No. of Clusters (Jockeys)	6,134	1,917	3,519	2,387	2,524	2,423
No. of Clusters (Horses)	114,883	42,357	64,599	30,268	51,040	23,634
No. of Observations	1,323,135	229,042	533,701	65,122	322,660	172,476

Regressions to establish whether female jockeys win more often than their odds imply, this time analysing different types of races. An indicator variable equalling 1 if the horse won the race, was regressed on the implied win probability of the horse (defined as $1/SP$ where SP is the starting price), and an indicator equalling 1 if a female jockey rode the horse. An OLS specification was used, heteroskedasticity-consistent standard errors (clustered for each jockey and each horse) are in parentheses, and *, **, and * indicates significance at the 0.1%, 1%, and 5% level respectively. The first regression uses data from all race types, with subsequent regressions examining all-weather flat racing, flat racing, national hunt flat races, hurdle races, and steeplechases.**

Table 5b: Positions (Race Type Sub-Samples)

Dep. Var.: Finishing Position	All	All-Weather Flat	Flat	NH Flat	Hurdle	Chase
Intercept	2.624***	2.730***	2.854***	2.888***	2.587***	2.174***
	(0.024)	(0.022)	(0.025)	(0.044)	(0.036)	(0.027)
Predicted Position	0.561***	0.535***	0.569***	0.606***	0.557***	0.425***
	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)
Female Jockey	-0.044	-0.123*	-0.100.	0.102	-0.543***	-0.300***
	(0.049)	(0.048)	(0.055)	(0.148)	(0.090)	(0.054)
R^2	0.333	0.288	0.322	0.376	0.358	0.269
No. of Clusters (Jockeys)	5,932	1,909	3,486	2,352	2,414	2,160
No. of Clusters (Horses)	111,821	42,239	64,346	29,681	46,425	19,852
No. of Observations	1,225,878	228,140	530,937	63,232	276,818	126,710

Regressions to establish whether female jockeys perform better than the betting market predicts, this time analysing different types of races. The finishing position of the horse, was regressed on the predicted finishing position of the horse (inferred from an ordering of the horses by betting odds), and an indicator equalling 1 if a female jockey rode the horse. An OLS specification was used, heteroskedasticity-consistent standard errors (clustered for each jockey and each horse) are in parentheses, and *, *, and . indicates significance at the 0.1%, 5% and 10% level respectively. The first regression uses data from all race types, with subsequent regressions examining all-weather flat racing, flat racing, national hunt flat races, hurdle races, and steeplechases.**

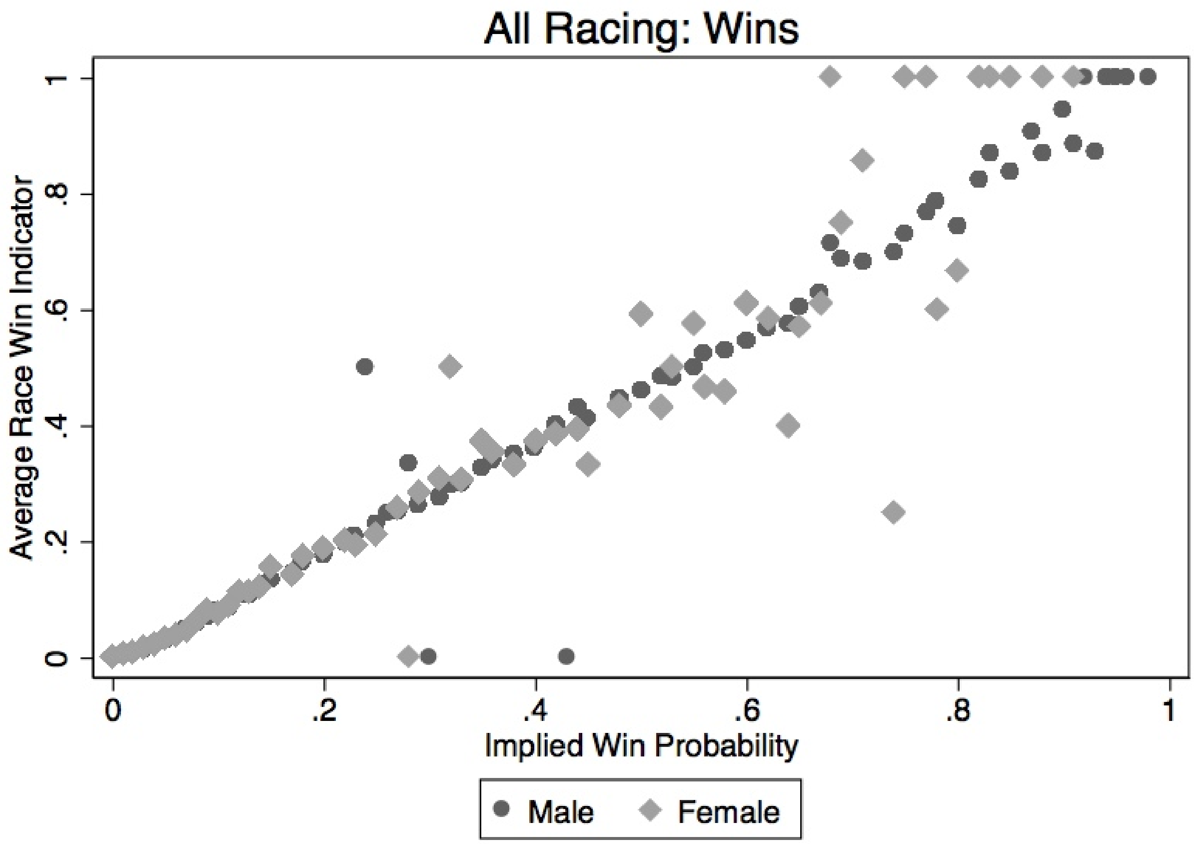

Figure 1: The average race win indicator (equalling 1 if the race was won, 0 otherwise) for male and female jockeys, plotted for each implied win probability (rounded to 2 decimal places). Implied win probability is defined as $1/SP$ where SP is the starting price, and data are taken from horse races in the U.K. and Ireland from 1st January 2003 to 7th September 2013 inclusive.

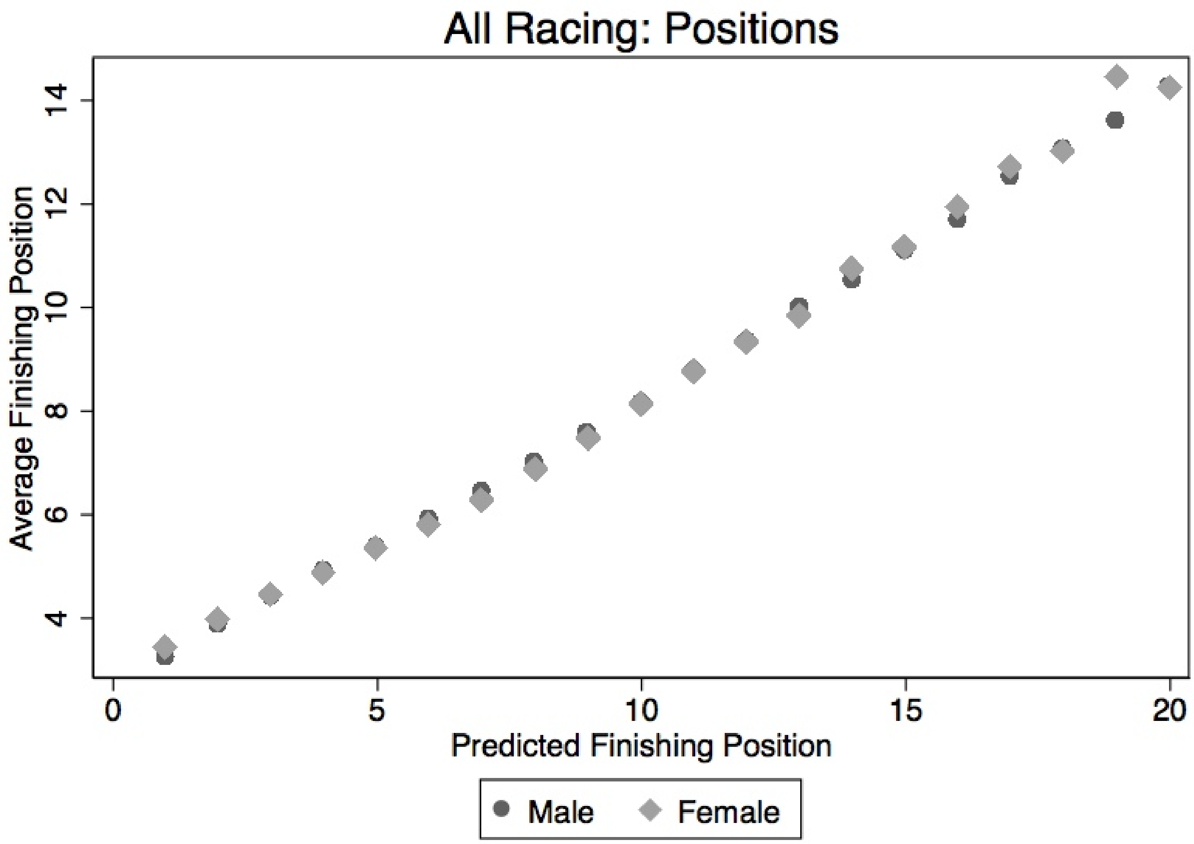

Figure 2: The average finishing position of male and female jockeys, plotted for each predicted finishing position (inferred by an ordering of horses by betting odds). Data are taken from horse races in the U.K. and Ireland from 1st January 2003 to 7th September 2013 inclusive, and only the top 20 predicted positions are displayed (few races have more than 20 participants).

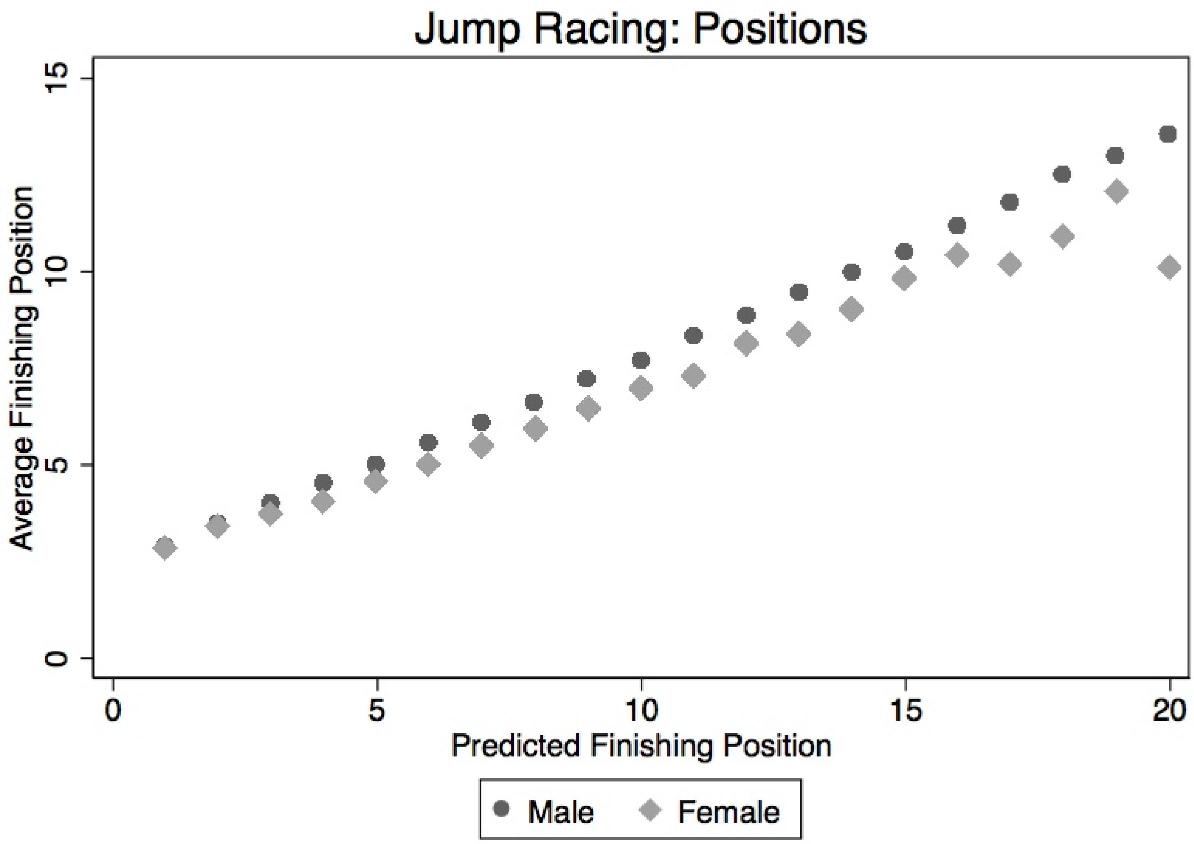

Figure 3: The average finishing position of male and female jockeys, plotted for each predicted finishing position (inferred by an ordering of horses by betting odds), this time just for jump racing (hurdles and steeplechases). Data are taken from horse races in the U.K. and Ireland from 1st January 2003 to 7th September 2013 inclusive, and only the top 20 predicted positions are displayed (few races have more than 20 participants).